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Climatic variability and thermal stress in Pakistan's rice and wheat systems: A stochastic frontier and quantile regression analysis of economic efficiency

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ABSTRACT

South Asia is the world's most poverty-dense region, where climate change and climate variability are expected to result in increased heat stress and erratic precipitation patterns that affect agricultural productivity. Considerable evidence has been generated on the effects of these stresses on crop yield, though previous research has not yet examined their influence on the economic efficiency of cereal producers. Surveying 240 farmers across eight of Pakistan's twelve agro-ecological zones, we examined the impact of temperature and precipitation anomalies – as indicators of climatic variability – and the number of days when temperature exceeds crop specific heat stress thresholds on the economic efficiency of rice and wheat production. To this end, we employed first-stage stochastic production frontier (SPF) models and second-stage ordinary least square (OLS) and quantile regression models. Both OLS and quantile regressions indicated that terminal heat > 34 °C has a significant negative impact on wheat production economic efficiency. Small positive deviation (0.54 °C ± 0.16 SD) of the wheat season's mean temperature from the medium-term historical mean also significantly and negatively affected economic efficiency across all regression models. Heat stress > 35.5 °C during rice flowering in the monsoon also had a significant and negative impact. A slight positive deviation in temperature averaging 0.38 °C (± 0.11 SD) above the medium-term mean also had significant negative effects across all regressions. Cumulative precipitation conversely had significant yet contrary effects, by offsetting farmers' investment in supplementary irrigation and increasing economic efficiency. Our results highlight the fact that indicators of climatic variability and heat stress negatively affect the economic efficiency of both rice and wheat producing farmers. Farmers' education and access to financial and extension services were however both positively associated with economic efficiency. Our findings point to the importance of developing interlinked agronomic, economic and socio-ecological policy strategies to adapt and increase the resilience of Pakistan's cereal systems to climatic variability.

1. Introduction

Ensuring food and livelihood security for an increasing global population in the face of climate change is one of the 21st century's most crucial humanitarian and scientific challenges. The global population is predicted to grow from 6.9 billion to 9.1 billion by 2050, with a potential increase in demand for food of up to 70% by 2050 (Godfray et al., 2010; Alexandratos and Bruinsma, 2012). Climate change is among the greatest challenges to achieve food and income security for the world's growing population (Wheeler and Von Braun, 2013; United Nations, 2012 United Nations, 2012). The potentially negative impacts of climate change on crop yield and farmers' livelihoods are predicted to increase the number of hungry people globally by 20% by 2050 (Carty and Magrath, 2013). A recent report by the World Bank states that over 100 million globally are at risk of falling into extreme poverty as a result of climate change over the next 15 years (Hallegatte et al., 2015).

The obstacles to achieving the goals of sustainable food and income

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security, are perhaps most prominent in the densely populated developing nations of the global south, where the majority of the world's food insecure people currently live (FAO, 2016). In the Asia-Pacific region alone, half a billion rural poor are subsistence farmers who are vulnerable to the effects of climate change and who are expected to experience negative impacts to their livelihoods (FAO, 2015). One third of global crop yield instability can be explained by climatic variability (Ray et al., 2015). Extreme weather events associated with climatic variability are also projected to increase with climate change, negatively affecting agricultural productivity in much of the tropics and subtropics (Rosenzweig et al., 2014). The globe's major cereals – rice (*Oryza sativa*), wheat (*Triticum aestivum*), and maize (*Zea mays*) – are all expected to experience general yield losses in these latitudes as a result of increasing temperatures, drought, flooding, and other extreme weather events (Bebber et al., 2013; FAO, 2016). When combined with poor governance, under developed markets, and limited civil and agricultural support services in many developing nations (Feder et al., 1985; Lee, 2005), climate-change induced crop losses could further worsen the food and income security status of many smallholder farming households (Schmidhuber and Tubiello, 2007).

These issues are particularly acute in South Asia, where approximately 30% of the globe's malnourished live (Lobell et al., 2008). As two of the region's most important crops, over 74 M ha in India, 12 M ha in Pakistan, 12 M ha in Bangladesh, and 2 M ha in Nepal are cropped to rice and wheat (FAOSTAT, 2017). In Pakistan, the productivity of the rice-wheat cropping sequence paramount to national food security. Rice and wheat, for example, contribute 5–10% and 50–60%, respectively, of average daily per capita calorific intake (WFP, 2010). Both crops are however susceptible to productivity declines under climate change. The food insecurity level in Pakistan is acute, with 82.6 million people – nearly half the country's population – suffering from hunger. Poorer households usually spend over 60% of their income on food and 36% of Pakistanis live below the poverty line (WFP, 2010).

The optimal thermal range for rice growth is approximately 27–32 °C (Shah et al., 2011). Temperatures above 32 °C approximately a week prior to or during anthesis can however result in decreased pollen viability and pollination. Embryo abortion and increased spikelet sterility can result, thereby lowering yields (Reynolds et al., 2016; Shah et al., 2011). The effects of terminal heat stress on the productivity of wheat in South Asia have been widely documented (Pfeiffer et al., 2005; Mondal et al., 2013; Krupnik et al., 2015a; Krupnik et al., 2015b). When temperatures exceed 30 °C, wheat photosynthesis can be disrupted, triggering the early onset of senescence and resulting in reduced grain filling and lower yields (Asseng et al., 2011; Reynolds et al., 1994; Lobell et al., 2012). Temperatures in excess of 32 °C during rice flowering can be more damaging, as reduced pollination, grain formation and filling can result (Farooq et al., 2011; Lobell et al., 2012; Reynolds et al., 2016; Shah et al., 2011). High temperatures also frequently coincide with drought stress, which is typically most severe if experienced in excess of 14 days during heading and early flowering. In both cases, decreased grain weight results (Reynolds et al., 2016).

As demonstrated by the above literature, most studies on the effects of climatic variability in South Asia focus on crop yields. In addition to providing the caloric basis for food security (WFP, 2010), wheat and rice are also important income generators for smallholder farmers in Pakistan, a country in which agriculture contributed 21% of GDP in 2015–16 (Govt. of Pakistan, 2016). Crop production in Pakistan generates roughly 43.5% of rural households' expendable income (Govt. of Pakistan, 2016). Wheat is Pakistan's most widely grown field crop, with over 25 million tons produced in 2014–15 (FAOSTAT, 2016), contributing 10% to agricultural value addition (Govt. of Pakistan, 2016). Rice is conversely Pakistan's second most prominent field crop, although mean yields have declined by 1.3 t ha^{-1} since 2009, resulting in a 30% loss in national production (FAOSTAT, 2016). The reasons for such decline appear to be related to rising temperatures, recurrent heat waves, flood events and consequent crop losses, in addition to high production costs which then affect farm income and farmers' livelihoods (Zahid and Rasul, 2012; Govt. of Pakistan, 2016).

This situation can have significant income implications in Pakistan, with potentially important ramifications for rural farm households' expenditures on health and child education, as well as in entrepreneurial investments, all of which affect development trajectories (Amjath-Babu et al., 2016; Govt. of Pakistan, 2016). Quantification of the effect of climatic variability on the economic efficiency of rice and wheat production is therefore warranted. This study responds to these issues and contributes to the literature on the effect of indicators of climatic variability and heat stress on crop productivity by analyzing how temperature and cumulative precipitation anomalies from medium-term climatic history and the number of days when temperature exceeds crop specific thresholds affect *ceteris paribus* the economic efficiency of wheat and rice farmers in Pakistan. In doing so, this paper breaks from more conventional analytical frameworks that treat indicators of climatic variability and heat stress as "given conditions" and that are inadequately represented as factors influencing farm efficiency performance. Employing a sample of 240 rice and wheat farmers across eight of Pakistan's leading cereal producing agro-ecological zones, our objectives were two-fold. We first sought to quantify the economic efficiency of both rice and wheat. In addition, we assessed if economic efficiency could be better explained through the inclusion of indicators of climatic variability and heat stress as independent variables in regression models.

2. Materials and methods

2.1. Primary data collection

Farm household surveys were conducted across eight of Pakistan's twelve rice and wheat producing agro-ecological zones (AEZs) as defined by PARC (2015) (Fig. 1). These AEZs were selected for study because they constitute some of the country's most important rice and wheat producing zones. In the next step, a disproportionate stratified random sampling technique was employed for primary data collection. Considering each AEZ as one stratum (cf. Arshad et al., 2015), surveys were conducted in eight districts randomly selected from within each of the eight AEZs studied. Two administrative units (referred to as *tehsils*) were then randomly selected from within each district. One village from within each *tehsil* was subsequently chosen at random, and from each village, 15 farm households were randomly selected for interviews. This resulted in 240 farm households. Surveys focussed on the prevailing socio-economic and farm characteristics of the sampled households, rice and wheat crop management information with emphasis on input use, resource access, and yield. Farmers' reports of rice and wheat sowing, flowering, and maturity date ranges were also recorded.

2.2. Secondary data collection, processing and threshold setting

We collected thirty-two years of temperature and precipitation data spanning the rice-wheat production seasons from November 1980 to October 2011 from the Pakistan Meteorological Department. Plotting mean seasonal temperature across station observations for the *kharif* and *rabi* seasons against the medium-term (1980–2011) seasonal mean revealed a general trend towards positive temperature anomaly after 2001 for both seasons, indicative of a gradually warming climate (Fig. 2). We further segregated all data into the *kharif* rice and *rabi* wheat production seasons, corresponding to early July to mid-October and November to early April to calculate the indicators of medium-term climatic variability, that is, the deviations of rice and wheat seasons' mean temperature and cumulative precipitation from historical data (Siddiqui et al., 2012).

We calculated cumulative precipitation received during each crop's growing season (sowing to maturity) and the number of days when

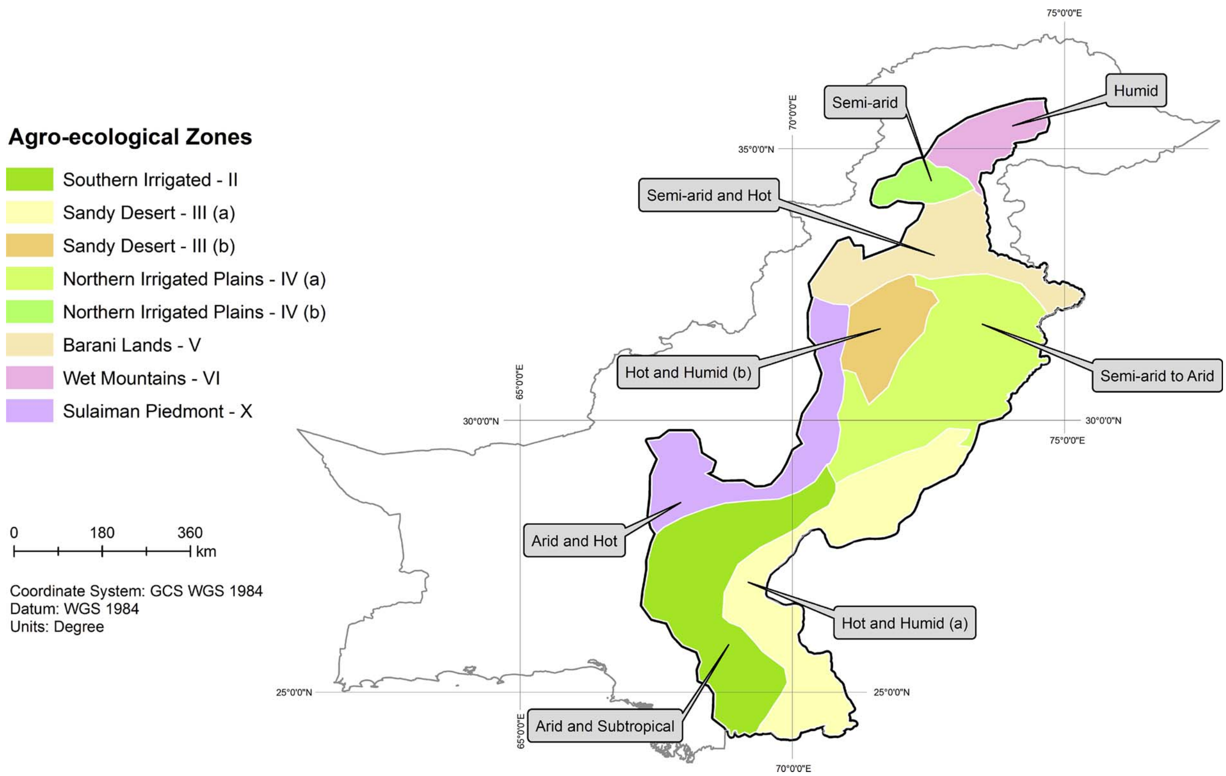

Fig. 1. Agro-ecological zones of Pakistan in which surveys were administered following PARC (2015).

temperatures exceeded phenologically sensitive heat stress thresholds on a locational basis, corresponding to farmers' reports of rice and wheat crop development, as indicators of heat stress. The cumulative number of days during which temperatures exceeded 30 °C, which is correlated with accelerated senescence (Asseng et al., 2011; Reynolds et al., 1994; Lobell et al., 2012), were for example calculated for wheat prior to flowering based on farmers' reports of phenology in 2011–2012 (the season in which surveys were administered). Terminal heat stress following the onset of flowering can also speed senescence and increase spike sterility. We therefore followed Lobell et al. (2012), Gourdji et al. (2013) and Hatfield et al. (2011) by calculating the cumulative number of days where temperature exceeded 34 °C during flowering and grain filling. For rice, the cumulative number of days during which temperatures exceeded 32 °C were tabulated following Krishnan et al., (2011) based on Yoshida (1978). This threshold is indicative of the upper limit for thermal stress-free growth for the entirety of the rice crop's life cycle. Rice can also however be sensitive to extreme heat during the reproductive phase. We therefore utilized a value of 35.5 °C as a threshold, calculated as the average from physiological field studies and reviews for rice conducted by Krishnan et al., 2011, Hatfield et al. (2011), Gourdji et al. (2013) and Shah et al. (2011), for the dates during which farmers reported flowering in 2012.

2.3. Methodological framework

We utilized a two-stage approach to analyse the relationship between climate variability and the economic efficiency of wheat and rice production in Pakistan. We first calculated efficiency scores for each farmer surveyed, and then regressed the estimated efficiency scores against a number of indicators of climatic variability and heat stress, socio-economic and farm variables. In the first stage, we employed a stochastic frontier production model to quantify economic efficiency (Coelli et al., 2005). We expressed all variables as economic values (i.e. costs of all input variables, including labour, and revenues from grain and straw sold) in order to estimate each farmers' economic efficiency by crop. Based on previous studies in Pakistan and Bangladesh, we also assume that farmers are cognizant of climatic variability and consequently adapt and adjust their crop management practices according to their experience of historical climate and crop productivity (Arshad et al., 2016b; Abid et al., 2016; Delaporte and Maurel, 2016). Through adjustments in crop management to minimize costs while maximizing productivity, farmers can attain increasingly economic efficient levels on the frontier. The Cobb and Douglas (1928) production function was employed in constructing the stochastic frontier. In the context of developing countries like Pakistan, farmers have motive to increase profits

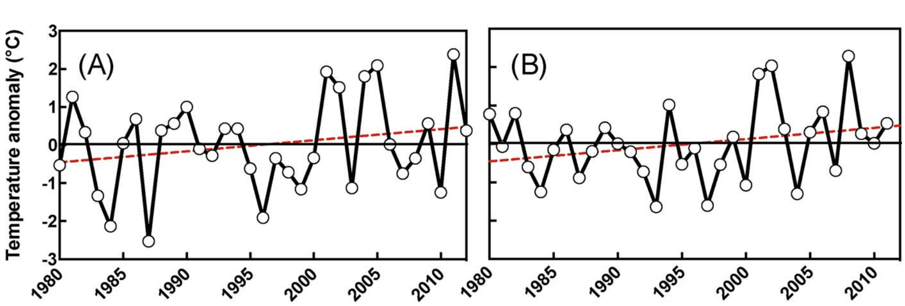

Fig. 2. Mean seasonal temperature anomaly from the medium-term (1980–2011) across eight agro-ecological zone meteorological stations in Pakistan. (A) During the winter *rabi* wheat production season, and (B) during the *kharif* monsoon rice season. The red dotted line indicates the generalized temperature anomaly trend. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

after household food security needs are met (Govt. of Pakistan, 2016).

In the second stage of analysis, ordinary least squares (OLS) and quantile regressions were employed to estimate the relationship between indicators of climatic variability and heat stress and farmers' efficiency scores. Quantile regression facilitates the estimation of the conditional quantiles of the response variable distribution, consequently providing a potentially more complete analysis of possible causal relationships between the response variable of interest (efficiency score) and explanatory climatic, socioeconomic, and farm characteristic data. In other more conventional analyses, indicators of climatic variability and heat stress have tended to be excluded (e.g. Parikh et al., 1995; Sharif and Dar, 1996; Battese et al., 1996).

2.4. Stochastic production frontier model

The stochastic production frontier model (SPF) model has been widely used to estimate the efficiency of a variety of crop production systems, including wheat and rice (Sharif and Dar 1996; Battese et al., 1996; Wadud and White, 2000). The generalized version of SPF for the i^{th} farmer can be written following Jondrow et al. (1982) as

$$Y_i = f(X_i; \beta) + \varepsilon_i, \; wherei = 1, 2, \ldots, n. \tag{1}$$

The error term in Eq. (1) can be further decomposed into random noise (v_i) and inefficiency(u_i), and rewritten as

$$Y_i = f(X_i; \beta).\, \exp(v_i).\, \exp(-u_i), \; wherei = 1, 2, \ldots, n \tag{2}$$

where X_i is the input vector of farmer i, Y_i is the single output of producer i, $f(X_i; \beta)$ is the deterministic component of the production function, where β is a vector of unknown parameters to be estimated, andexp(v_i) is the stochastic component of the production function that accounts for statistical noise. SPF model assumes a symmetric distribution with a mean of zero. Finally, $u_i$is the second error term capturing inefficiency, assumed to be independent of v_i so as to satisfy the restriction $u_i \geq 0$. The SPF analysis results in economic efficiency scores (θ) alongside with parameter estimates(β).

Following Lovell (1993), we computed (θ) as

$$\theta_i = \frac{Y_i}{[f(X_i; \beta).\, \exp\{v_i\}]} = \exp\{-u_i\}, \; i = 1,2, \ldots, n. \tag{3}$$

and tested two specifications for $f(X_i; \beta)$ in Eq. (2), including the Translog specification compared against the Cobb-Douglas specification. A likelihood ratio test rejected the former at $\alpha = 5\%$. We consequently estimated Cobb-Douglas production function $f(X_i; \beta)$ by taking the natural logs of both sides of Eq. (1). The direct elasticity of the variables was estimated with this production function. The log linear functional form can therefore be written as follows:

$$\log Y_i = \beta_0 + \beta_1 \log X_{1i} + \beta_2 \log X_{2i} + \beta_3 \log X_{3i} + \beta_4 \log X_{4i} + \beta_5 \log X_{5i} + B_6 \log X_{6i} + \beta_7 \log X_{7i} + (V_i - U_i) \tag{4}$$

where Y_i represents gross revenue hectare^{-1}, X_i is a vector of physical inputs and farm production information – i.e. rice or wheat area (X_{1i}), seed cost (X_{2i}), fertilizer cost (X_{3i}), pesticide cost if any (X_{4i}), irrigation costs (X_{5i}), total land preparation (tillage, levelling, planking, seed incorporation) and labour costs (X_{6i}),[1] and land rent where applicable (X_{7i}). $\beta_0$is a constant. The terms β_1 through β_7 are unknown parameters to be estimated. v_i is a random error term that we assume to be independent and identically distributed as $N(0, \sigma_v^2)$, while u_i is a one-sided inefficiency component, assumed to be a non-negative half normal distribution as $N(0, \sigma_u^2)$ and $i = 1, 2, \ldots\ldots\ldots n$ (total number of farmers of the corresponding rice or wheat crop). Maximum likelihood estimates of the parameters and θ were derived using the 'Frontier Package 1.0' in R version 3.1.1 (Coelli and Henningsen, 2013). The monetary values of all the variables used in our analyses were converted into US Dollars at 1USD = 106 PK following mean 2012 exchange rates.[2]

2.5. OLS and quantile regression models

In the second stage of analysis, we employed OLS and quantile regressions to capture the effects of the observed cropping seasons' critical rice and wheat phenological stages to indicators of heat stress and cumulative precipitation measurements. Deviations of cropping seasons' mean temperature and cumulative precipitation from medium-term mean historical data (indicators of climatic variability) on farmers' economic efficiency scores were also examined. In both regression models, we assumed that farmers adjust their cropping practices and management decisions to increase efficiency in response to within-season climatic variation, and consequently to the deviation of observed cropping seasons' mean temperature and cumulative precipitation from the medium-term mean. All farmers included in the analyses were therefore active in agricultural production for at least 32 years prior to surveys in 2012.

The logic behind including both the temperature and precipitation data for the observed cropping seasons, as well as the deviation from medium-term historical averages, is that economic efficiency is at least partly determined by the crop's response to current weather conditions and as well as by farmers' crop management decisions that interact with and can mediate the influence of climate (Arshad et al., 2016a; Arshad et al., 2016b; Abid et al., 2016). Farmers have been widely observed to adapt their management practices based on what they perceive of as climatic anomalies. Adaptation techniques can include crop species choice, modification of sowing dates, choice if cultivars, input use and timing, and supplemental irrigation, among others (cf. Smit et al., 1996; Abid et al., 2016).

The quantile regression model is a robust alternative to classical OLS regression (Koenker and Bassett, 1978; Leider, 2012), and is well suited to addressing the complexity of the relationships between numerous explanatory and the response variables. Simple linear regression estimates the mean rate of change of the response variable as a conditional function of one or several explanatory variables (Montgomery et al., 2015). Quantile regression, however, extends this estimation to any part of the response variable's distribution, i.e. to any selected quantile, thereby facilitating a clearer interpretation of the relationship between variables that may otherwise have weak or no relation. As such, quantile regression allows the simultaneous study of changes in specific portions of the distribution of the response variable to independent variables independently of the change and variability experienced by the rest of the distribution. Further details on the use of quantile regression for datasets of this kind can be found in Koenker (2005) and Koenker and Hallock (2001). The use of quantile regression to estimate variation in median and quantile responses therefore renders it suitable for more nuanced study of the impacts of climatic variability on crop production and economic efficiency (Chamaillé-Jammes et al., 2007). We therefore augment the results obtained from more conventional OLS regression with those produced by quantile regression by estimating parameters for the four quantiles 0.25, 0.50, 0.75 and 0.95.

In both OLS and quantile regression models, the economic efficiency scores of rice and wheat production are regressed on the set of temperature thresholds for crop stress at specific phenological states and indicators of climatic variability as described in Section 2.2. Cumulative precipitation was also examined, alongside control variables including socio-economic, crop management, and farm variables (Appendix A). Landmark studies in the early 1990s applying SPF models analysed how key socio-economic factors and farm characteristics such as farm size,

[1] Total labour costs are calculated as the sum of eight-hour work days required for all crop establishment, maintenance, and harvest operations for rice or wheat independently.

[2] Mean exchange rate is available at: http://www.exchangerates.org.uk/.

provision of extension services and farmers' educational levels influenced the relative efficiency of crop production in Pakistan (Parikh et al., 1995). These considerations were therefore included in our analysis.

We first fitted an OLS multiple regression model on a set of predictor variables (z_i), including selected socioeconomic, crop management, farm characteristic, and climatic data, in order to discern the impact of the latter on economic efficiency(θ_i), as;

$$\theta_i = \hat{\beta}_0 + \hat{\beta}_1 z_{i1} + \ldots + \hat{\beta}_{in} z_{in} + \hat{u}_i \quad (5)$$

We then fitted the quantile regression as suggested by Koenker and Bassett, (1978):

$$\theta_i = X_i^T + \beta_\tau, + \mu_{\tau i}, \ \mu_{\tau i} \sim D_{\tau i} \ \textit{subject to} \ D_{\tau i}(0) = \tau \quad (6)$$

where θ_i is the dependent variable (efficiency score) computed from the stochastic production frontier model in step one. While 'i' in Eq. (6) is the index of individual farmers, 'X' represents the vector of covariates for 'i'. The quantile specific effects is given by β_τ for a given quantile: $0 < \tau < 1$. The unknown error term '$\mu_{\tau i}$' above is characterized by cumulative distribution function '$D_{\tau i}$'. The quantile regression model in Eq. (6) explains the quantile function $Q_{\tau i}(\tau|X_i)$ of the dependent variable 'θ_i' conditioned on a vector of independent crop specific climatic indicator variables 'X_i' at a given quantile 'τ'. The quantile function can be specified as:

$$Q_{\tau i}\left(\tau X_i\right) = D_{\theta_i}^{-1}\left(\tau X_i\right) = X_i^T \quad (7)$$

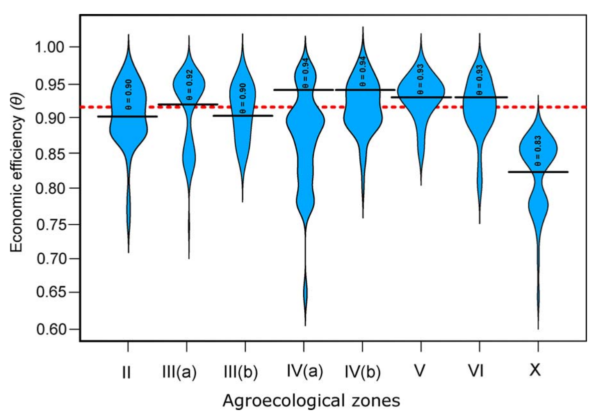

Fig. 3. Bean density plots depicting the economic efficiency (θ) of surveyed wheat farmers within eight agro-ecological zones of Pakistan. Bean shape is a left-right symmetrical image of the each AEZ's density plotted vertically. Solid black horizontal lines indicate the efficiency mean for each AEZ, while the dotted red horizontal line represents mean θ across AEZs. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The conditional quantile can also be expressed as an optimization problem (Koenker and Bassett (1978) given below :

$$\underset{\beta_\tau}{\text{argmin}} \sum_{i=1}^{n} \rho_\tau(\theta_i - X_i^T \beta_\tau) \quad (8)$$

where 'ρτ (.)' is the "check function" that weights positive and negative terms of a quantile asymmetrically. The Eq. (8) is solved either by linear programming or estimated by maximum likelihood estimation using "quantreg" package in R.

3. Results and discussion

3.1. Stochastic frontier estimates

Stochastic frontier estimates indicated that the mean economic efficiency for wheat and rice production in 2011–12 was 91% and 93%, respectively. These results are consistent with previous studies in South Asia's rice-wheat systems. While Rahman and Rahman (2009) for example reported 91% for the efficiency of monsoon *aman* season rice production in Bangladesh, Krishna and Veettil (2014) and Aravindakshan et al. (2015) estimated a similar average efficiency of 90% for wheat under conservation tillage in India and Bangladesh, respectively. We further disaggregated efficiency scores of rice and wheat farmers' across the agro-ecological zones. We visually compared the efficiencies of farmers using bean density plots (cf. Kampstra, 2008; Aravindakshan et al., 2015) shown in (Figs. 3 and 4). In the case of wheat, while the lowest average efficiency score was observed in AEZ X (0.83), AEZs IVa and IVb recorded the highest economic efficiency (both 0.94). In the case of rice, farmers in AEZs II and IVa recorded the highest average efficiencies (0.96 and 0.95, respectively), while AEZs (IIIa, IIIb and X) had the lowest efficiency (0.92). The mean efficiencies across AEZs were however not significantly different ($P > 0.01$) when subjected to a t-test assuming unequal variance.

Parameter values resulting from the maximum likelihood estimates of the stochastic frontier production function can also be interpreted as partial production elasticities (Chidmi et al., 2011). A positive return to scale (1% increase in land area cultivated increases gross revenue per hectare by 3% for wheat and 2% for rice) was observed, indicating important economies of scale. Our findings support previous literature on efficiency studies indicating a positive relationship between land area cultivated and value of production (Jha et al., 2000). These results however should be interpreted cautiously. The coefficients of fertilizer, irrigation (evident more in the case of rice), and labour also indicate that an increase in these inputs can improve economic performance (Table 1). Few farmers in our sample however used these inputs near recommended levels, and as such we were unable to quantify the point at which economic efficiency may plateau following increased input use, for example through diminishing marginal return to fertilizer use

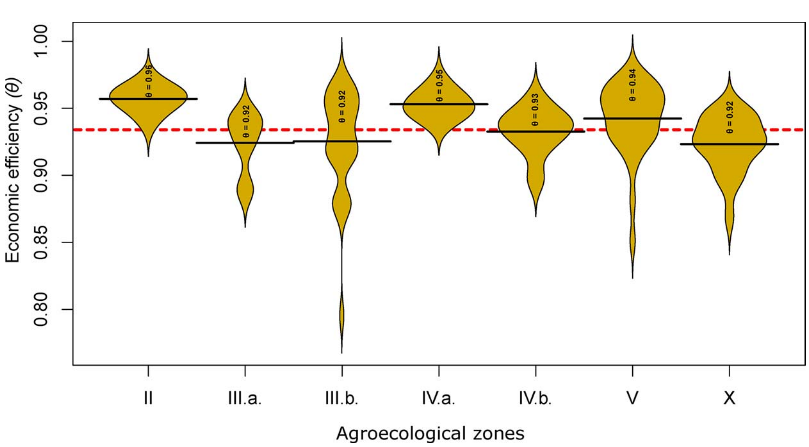

Fig. 4. Bean density plots depicting the economic efficiency (θ) of surveyed rice farmers within eight agro-ecological zones of Pakistan. For further details, see the legend for Fig. 3.

Table 1
Stochastic production frontier estimates of wheat and rice production.

Variable	Unit season^{-1}	Wheat		Rice	
		Mean (SD)	SPF estimates (SE)	Mean (SD)	SPF estimates (SE)
Area under cultivation[a]	ha	2.9211 (3.01)	0.0337 (0.01)**	3.2811 (2.93)	0.0247 (0.01)
Seed cost[a]	USD ha^{-1}	41.1421 (7.36)	0.0838 (0.04)	15.3112 (3.00)	−0.0352 (0.04)
Nutrient addition cost[a,b]	USD ha^{-1}	190.2916 (64.27)	0.2688 (0.02)***	214.4321 (74.08)	0.2520 (0.02)***
Pest control cost[a]	USD ha^{-1}	8.7124 (10.71)	0.0030 (0.00)**	14.2631 (16.63)	0.0014 (0.00)
Irrigation cost[a]	USD ha^{-1}	62.2422 (22.16)	0.0023 (0.00)***	211.1833 (33.97)	0.1649 (0.06)**
Land preparation and total labour cost[a]	USD ha^{-1}	207.4010 (40.13)	0.0792 (0.04)	312.1016 (41.03)	0.2820 (0.07)***
Land rent[a]	USD ha^{-1}	191.1630 (59.65)	0.2646 (0.03)***	70.0302 (96.56)	0.0005 (0.00)
σ^2			0.0143 (0.00)***		0.0128(0.00)**
Gamma (γ)			0.8076 (0.13)***		0.5964 (0.26)*
Mean economic efficiency (θ)			0.91		0.93

Notes: For brevity, the model intercept is not shown. Standard deviations (SD) of the mean and standard errors (SE) of coefficient estimates both are shown in parentheses. Mean gross revenue per hectare for wheat is 901.70 USD and rice is 1109.683 USD ha^{-1}, with standard deviations of 170.31 and 149.86 USD, respectively.
*, ** and *** indicate significance at $P \leq 0.10$, 0.05, and 0.001.
[a] Natural log.
[b] Includes primarily inorganic nitrogen, phosphorous, and potassium addition. Use of organic fertility amendments was rare and disregarded.

efficiency (Krupnik et al., 2004). Further work to quantify these effects under farmers' own management practices is therefore needed in Pakistan prior to advising on land consolidation or larger farm sizes as a mechanism to boost agricultural productivity.

These findings have important implications for policies to 'sustainably intensify' crop productivity using methods that increase efficiencies (and hence limit environmental externalities) without increasing cultivated land area. This objective is crucial to maintain non-agricultural biodiversity and to limit agricultural encroachment into natural ecosystems (Krupnik et al., 2017; Quinn et al., 2016; Garnett et al., 2013; FAO, 2014). Our data indicate that increased input use is likely to increase productivity and economic efficiency, although this tendency is only likely to a point after which input use (nutrients in particular) is likely to decrease efficiency, thereby reducing economic performance (Krupnik et al., 2004). Increased use of inputs should also be accompanied by careful use of agronomic best management practices (e.g., correct fertilizer rates and application timing, judicious use of irrigation, weeding practices to limit productivity losses, long-term efforts to sustain soil organic matter and the agricultural resource base); without such management, increased input use could result in heightened environmental externalities that ultimately undermine sustainable intensification (Patra et al., 2016; FAO, 2014). Policies to increase rice and wheat farmers' economic efficiency while avoiding non-agricultural land area conversion are therefore likely to benefit from increased attention to the promotion of sound agricultural practices that maximize productivity per unit of external input use, so long as grain markets remain relatively stable. The market price of wheat grain has been relatively stable in the recent years in Pakistan as compared to rice. The latter increased 10.29% from 2015 to date, mainly as a result of yield instability resulting from climatic variability while per capita demand changed little (Govt. of Pakistan, 2017; FAOSTAT, 2016).

3.2. Climate variability and the economic efficiency of wheat production

OLS regression model estimates indicate that terminal heat > 34 °C had a significant ($P < 0.001$) and negative effect (coefficient −0.042) on the economic efficiency of wheat for the sampled farmers in Pakistan. Temperatures in excess of this threshold were recorded for an average of 0.7 (± 0.5 SD) days during wheat's flowering and grain filling periods, mirroring evidence on the detrimental effects of terminal heat stress elsewhere in South Asia (Mondal et al., 2013; Krupnik et al., 2015a; Krupnik et al., 2015b). The cumulative number of days during which wheat experienced high temperatures > 30 °C (20.0 ± 8 SD) however had no significant effect, although it negatively affected the efficiency of wheat farmers in the upper most quantile (Table 2). Total cumulative precipitation (388 ± 173 mm SD) also had no significant effect in the OLS regression, likely because of wheat farmers' tendency to offset soil moisture deficits with irrigation averaging (4.91 ± 4.03 SD) applications season^{-1}, as shown by Arshad et al. (2016a). Cumulative precipitation however did positively and significantly affect wheat farmers in the 50th and 75th quantiles, at $P < 0.05$ and 0.1, respectively.

The negative relationship between critically high temperature late in the wheat crop's phenology, and the declining efficiency of the conversion of investments in crop management and inputs into revenue partially results from yield decline (Mondal et al., 2013). Wheat production in Pakistan however averaged 2.78 t ha^{-1} in the year of our surveys, 0.33 t ha^{-1} less than mean yields reported by farmers in our dataset (FAO, 2016). Further research is therefore warranted with a larger sample size to confirm if our observed effects hold for farmers who may be operating at lower agronomic productivity levels.

The deviation of the *rabi* season's mean temperature from the medium-term historical mean, which averaged a small 0.54 °C increase (± 0.16 °C SD) in non-quantile estimates, also showed highly significant and negative effects (coefficient −0.14, $P < 0.01$) on the economic efficiency of wheat production in the OLS regression. The same trend was observed for each quantile of the quantile regression (coefficient range −0.14 (25th quantile) to −0.24 (95th quantile), all $P < 0.01$). These relatively robust results also suggest that positive temperature anomalies – even at relatively low levels – can have a strong negative effect on wheat production efficiency when they ocurr during critically sensitive periods of crop phenology. Deviation in precipitation, which averaged an 16.28 mm increase (± 8.51 mm SD), however did not show any significant effect.

The impacts of heat stress during the wheat flowering stage on the economic efficiency of farmers across all quantiles were negative, supporting the literature on the general importance of wheat's susceptibility to increased temperatures in the tropics and sub-tropics (Farooq et al., 2011; Mondal et al., 2013). A number of agronomic solutions to heat stress have been validated and extended to South Asia's wheat farmers. These include use of heat-tolerant and short-cycle varieties that mature prior to the onset of critically high temperatures (Mondal et al., 2013; Krupnik et al., 2015b), early sowing and reduced tillage with innovative equipment (which can accelerate sowing time) to escape from high temperatures (Sultana et al., 2009; Krupnik et al., 2013), use of short-duration monsoon *kharif* season rice varieties and mechanical rice harvest to move forward subsequent wheat sowing dates, and supplemental irrigation to modify canopy temperature relative to atmospheric temperature (Krupnik et al., 2015a), among others. Where farmers are unable to implement these techniques,

Table 2
Ordinary least squares (OLS) and quantile regression estimates for the economic efficiency of wheat production.

Variable	OLS Estimates	Quantile regression estimates			
		0.25	0.50	0.75	0.95
Education of the household head (years)	0.0846***	−0.0002***	0.0004**	0.0003	0.0665***
Age of the household head (years)	0.0158	0.0003	−0.0005	−0.0007*	0.0018
Household size (number of household members)	−0.0001	0.0010	0.0007	0.0017	0.0012***
Total cultivated area (ha)	−0.0471**	0.0006	−0.0007***	−0.0004	−0.0007***
Access to extension services (dummy)	0.0757***	0.986***	0.966***	1.001***	0.939***
Access to credit services (dummy)	−0.0125	0.0002***	0.0127	−0.0066	0.0001**
Soil types (dummy)[a]	0.0111	0.0001	0.0006	0.0002	0.0003
Cumulative precipitation during the wheat cropping season (mm)	0.0018	0.0001	0.0001**	0.0353*	0.0036
Days from sowing to maturity in wheat with temperatures > 30 °C (n)	9.06e-07	−0.0009	0.0005	0.0006	−0.0008***
Days during wheat flowering with daytime temperatures > 34 °C (n)	−0.0426***	−0.0529**	−0.0359***	−0.0425***	−0.0161***
Deviation of the wheat season's mean precipitation from the historical mean (mm)	−0.0001	-4.84e-05	−0.0002	-8.84e-05	−0.0002
Deviation of the wheat season's mean temperature from the historical mean (°C)	−0.140***	−0.140***	−0.142***	−0.167***	−0.237***
Constant	60.93	74.06	62.38	67.62	57.29
R^2	0.68	0.21	0.19	0.17	0.33
Total observations (n)	240				

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.
[a] Denotes clay or non-clay soil textures.

diversification out of wheat and into other income generating crops or livelihood pursuits that can simultaneously contribute to food security may be a sensible adaptation.

In addition to indicators of climatic variability, farmers' education level, access to credit and extension services positively influenced economic efficiency, for reasons similar to those previously discussed by Arshad et al. (2016a, 2016b) in Pakistan, and Aravindakshan et al. (2016) in Bangladesh. Extension in particular had a significant influence on efficiency in both the OLS and quantile regressions at all quantile levels (all $P < 0.001$). These results further imply the importance of bringing together national meteorological and rural extension departments to enhance capacity building. Further efforts to effectively communicate climate information through agricultural climate services initiatives, and to implement adaptation policies across sectors relevant to farm productivity, are also likely to be needed (Vincent et al., 2015).

3.3. Climate variability and the economic efficiency of rice production

OLS model estimates (Table 3) show that the total number of days during rice flowering with temperatures above 35.5 °C was 14.12 days (± 7.52 SD). This indicator had a negative (coefficient −0.019) and significant ($P < 0.01$) effect on rice farmers' economic efficiency. The effect of number of days from rice sowing to maturity with temperatures > 32 °C (mean 88.62 days ± 11.88 SD) was however insignificant. Cumulative precipitation received during the cropping season (mean 421 mm ± 193 SD) conversely significantly increased the efficiency of rice crop production. This is likely because reliable rainfall can reduce the need for supplementary irrigation in rice (Cornish et al., 2015), thereby lowering production costs and increasing profitability.

As with wheat, our results suggest that indicators of climatic variability and heat stress are important determinants of economic efficiency in *kharif* monsoon season rice production. Although the deviation in cumulative precipitation in the study year from the medium-term mean was low (26.19 mm ± 14.42 SD) and showed no effect, a very slight positive deviation in temperature (mean 0.38 °C ± 0.11 SD) was conversely consistently significant (all $P < 0.01$), with negative effects in both the OLS and all quantiles of the subsequent regression. These results are somewhat surprising as rice tends to be less sensitive to increased temperatures than wheat (Reynolds et al., 2016), although high night time temperatures can contribute to yield decline in rice (Peng et al., 2004). Temperatures exceeding the 32 °C threshold during the early reproductive stage can also negatively impact yield by reducing pollen production and deposition, successful fertilization, and grain development (Reynolds et al., 2016; Krishnan et al., 2011; Shah et al., 2011), with implications for economic efficiency.

Because the wheat and rice are usually grown in an annual rotational pattern on the same field, the same group of farmers growing wheat were surveyed with respect to their rice production practices. Our survey data showed that farmers however tended to devote more land area to *kharif* monsoon season rice production (0.35 ha greater on average) than to wheat (Appendice A) Data indicate that this is likely because *basmati* rice usually has more favorable market prices than wheat in Pakistan (Govt. of Pakistan, 2016). As with wheat, farmers' degree of formal education – which averaged just 2.64 years (± 4.19 SD) had a significant ($P < 0.01$) and positive influence on economic efficiency in the OLS regression. Similar results were obtained in quantile regressions, with the exception of the 50th quantile. Access to extension services however had a significant (all $P < 0.01$) and positive effect on economic efficiency in all regression models.

Implicit in our study are assumptions that farmers observe medium-term climatic patterns, and that they actively adapt to changing meteorological circumstances in order to boost production efficiency. Feola et al. (2015) studied farmer adaptation to climate change in South and North America, and in South and South East Asia. Their results highlighted the importance of cross-scale and cross-level pressures in adaptation processes. In the case of the current study, we highlighted the cross-scale effects of changing temperature and precipitation patterns by examining the deviation of the study year from the medium-term mean. Cross-level pressures were examined by studying the ways in which crop-stress inducing temperature thresholds affected economic efficiency. Researchers wishing to build on our work may want to consider the potential canopy temperature mediating effects of vapor pressure deficit, which could affect crop stress and economic efficiency. We were, however, unable to account for this variable in the current study due to meteorological data limitations. These results are therefore of preliminary value, and further efforts are needed to fully understand and improve upon farmer adaptation behaviour.

Table 3
Ordinary least squares (OLS) and quantile regression estimates for the economic efficiency of rice production.

Variable	OLS Estimates	Quantile regression estimates			
		0.25	0.50	0.75	0.95
Education of the household head (years)	0.0055***	0.0027**	0.0004	0.0013*	0.0010***
Age of the household head (years)	0.0050	0.0004	−0.008	−0.0002	−0.0050**
Household size (number of household members)	-1.00e-05	0.0004	0.0016	0.0002	0.0006***
Total cultivated area (ha)	−0.0032**	−0.0449*	−0.0283*	0.0001	−0.0001**
Access to extension services (dummy)	1.135***	0.0001***	0.0596**	0.0288***	0.0086***
Access to credit services (dummy)	0.0052	0.0122	−0.0035	0.0066	0.0086***
Soil types (dummy)[a]	−0.0208	−0.0004	−0.0001	−0.0104	0.0001
Cumulative precipitation during the rice cropping season (mm)	0.0027*	0.0001*	0.0002**	4.50e-05	2.78e−05***
Days from sowing to maturity in rice with temperatures > 32 °C (n)	−0.0022	−0.0039	1.33e-06	−0.0020	−0.0001
Days during rice flowering with daytime temperatures > 35.5 °C (n)	−0.0195***	−0.0013***	−0.0037**	−0.0029**	−0.0024***
Deviation of the rice season's mean precipitation from the historical mean (mm)	−0.0001	−0.0002	0.0075	-1.55e-05	-9.86e-07
Deviation of the rice season's mean temperature from the historical mean (°C)	−0.0018***	−1.290***	−1.396***	−1.102***	−1.035***
Constant	1.13	−2.94	−6.96	−4.87	−6.79
R^2	0.76	0.19	0.22	0.17	0.29
Total observations (n)	240				

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.
[a] Denotes clay or non-clay soil textures.

In addition to cross-scale and cross-level pressures, Feola et al. (2015) for example highlighted the importance of integrated studies that include assessment of farmers' decision making models (that recognize the embeddedness of social and biophysical factors, including social networks and power relations), and temporal dynamics (how farmers' behaviour change or is replicated or changes over time). The ways in which production elasticities affect farmers' willingness to adapt to climate variability and thermal stress are also relevant, though beyond the scope of our study. To this end, further research to develop panel data and include detailed study of farmers' decision making processes with respect to adaptation choices and their consequent impact on economic efficiency is urgently needed. Studies such as this could provide rich and continual feedback of relevance to policy makers concerned with increasing climate change adaptation capacity in Pakistan and South Asia.

4. Conclusions

This study contributes to the literature on the impact of climate variability and thermal stress in Pakistan's cereal production systems in several ways. We estimated the impacts of the indicators of season-long and terminal heat stress, cumulative precipitation, and temperature and precipitation deviations from the medium-term mean (indicators of climatic variability) on the economic efficiency of rice and wheat farmers across eight of Pakistan's twelve agro-ecological zones. Unlike prior studies considering the generalized economic impacts of climate change on crop production, we examined the effect of exposure both crops to species-specific temperature thresholds during their growth and reproductive stages. Our results indicate that terminal heat stress and increased climatic variability can negatively affect the economic efficiency of wheat and rice farmers in Pakistan, with important policy implications for efforts to boost both rural income and food security.

These results highlight the importance of developing more climate-smart agricultural policies – with strong emphasis on the need for adaptation to thermal tress – in Pakistan's cereal production systems. Technical priorities are likely to include stress tolerant rice and wheat genotypes, as well as crop and management practices that allow farmers to escape from the detrimental effects of increasing temperature, including reduced tillage for earlier sowing, short-cycle cultivars, mechanical harvesting of monsoon season *kharif* rice to accelerate subsequent wheat season sowing dates, supplementary irrigation, and plant growth regulators, among others. These agronomic approaches are however unlikely to be independently sufficient. Additional research into farmer decision processes that integrate biophysical, physiological and socio-economic considerations are also needed to inform and guide the extension of technological approaches. Given the potential consequences of decreased cereals production and reduced farm incomes, the latter of which can have important secondary and negative effects on household expenditure for education and health care, viable adaptation measures are required. Our results also highlight the importance of agricultural development policies aimed at increasing farmers' access to extension and financial services, in addition to basic education, all of which are likely to be prerequisite to the successful and durable implementation of agronomic adaption strategies in Pakistan. Similar studies may also be replicated elsewhere in South Asia to validate our results, and to gain a more comprehensive picture of the impacts of thermal stress and climatic variability on the economic efficiency of rice and what production, especially where panel farm productivity data are available in addition to meteorological records.

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Appendix A

See Tables A1 and A2.

Table A1
Summary statistics of explanatory variables in the regression models for wheat

Variable description	Non-quantile		Quantile			
	Mean	SD	25%	50%	75%	95%
Response variable						
Efficiency Score	0.91	0.04	0.89	0.93	0.94	0.96
Predictor variables						
Socioeconomic and farm variables						
Education of the household head (years)	2.64	4.19	0.00	0.00	5.00	11.00
Age of the household head (years)	53.70	12.59	47.00	55.00	62.50	71.00
Household size (number of household members)	12.32	4.63	9.00	11.00	15.00	20.50
Total cultivated land (hectare)	2.93	2.72	1.60	3.60	4.40	6.00
Access to extension services (dummy)	0.59	0.49	0.00	1.00	1.00	1.00
Access to credit services (dummy)	0.68	0.47	0.00	1.00	1.00	1.00
Soil type (dummy)[a]	0.31	0.47	0.00	0.00	1.00	1.00
Climate variables						
Cumulative precipitation received during the wheat cropping season (mm)	387.95	173.06	198.5	245.8	432.4	605.7
Days from sowing to maturity in wheat with temperatures > 30 °C (n)	20.00	8.01	11.50	19.00	26.00	32.00
Days during wheat flowering with daytime temperatures > 34 °C (n)	0.65	0.48	0.00	1.00	1.00	1.00
Deviation of the wheat season's mean precipitation from the historical mean (mm)	16.28	8.51	0.83	14.58	33.81	81.39
Deviation of the wheat season's mean temperature from the historical mean (°C)	0.54	0.16	0.35	0.47	0.66	0.87

SD indicates standard deviation.
[a] Denotes clay or non-clay soil textures.

Table A2
Summary statistics of explanatory variables in the regression models for rice

Variable description	Non-quantile		Quantile			
	Mean	SD	25%	50%	75%	95%
Response variable						
Efficiency Score	0.93	0.02	0.90	0.92	0.94	0.96
Predictor variables						
Socioeconomic and farm variables						
Education of the household head (years)	2.64	4.19	0.00	0.00	5.00	11.00
Age of the household head (years)	53.70	12.59	47.00	55.00	62.50	71.00
Household size (number of household members)	12.32	4.63	9.00	11.00	15.00	20.50
Total cultivated land (hectare)	3.28	2.24	1.30	3.80	5.20	7.10
Access to extension services (dummy)	0.59	0.49	0.00	1.00	1.00	1.00
Access to credit services (dummy)	0.68	0.47	0.00	1.00	1.00	1.00
Soil type (dummy) [a]	0.31	0.47	0.00	0.00	1.00	1.00
Climate variables						
Cumulative precipitation during the rice cropping season (mm)	421.40	193.41	288.2	320	507.9	740.70
Days from sowing to maturity in rice with temperatures > 32 °C (n)	88.62	11.88	79.00	89.00	99.00	104.00
Days during rice flowering with daytime temperatures > 35.5 °C (n)	14.12	7.53	5.00	12.00	21.00	22.00
Deviation of the rice season's mean precipitation from the historical mean (mm)	26.19	14.43	−63.87	12.56	60.59	67.98
Deviation of the rice season's mean temperature from the historical mean (°C)	0.38	0.11	0.16	0.21	0.23	0.36

SD indicates standard deviation.
[a] Denotes clay or non-clay soil textures.

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